



Assessment of the urban heat island in the city of Tehran using reliability methods

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ARTICLE INFO

Keywords:

Urban Heat Island
Reliability framework
WRF-ARW
Downscaling methods
Bayesian regression

ABSTRACT

Climate change affects temperature, magnitude, and also the duration of the Urban Heat Island (UHI), which has severe impacts on the environment, communities, and the people's lives. This study evaluates UHI formation in the city of Tehran (Iran) using a reliability framework, which is able to include related uncertainties into the modeling procedure. First, 2 km air temperature field from Weather and Research Forecasting (WRF) model is downscaled to a 50 m grid spacing using a probabilistic downscaling method, which combines inverse distance weighting (IDW) interpolation and a Bayesian regression model. This downscaling method not only can produce a long record of the fine resolution of the temperature but also improves the WRF temperature outputs' accuracy. The downscaled temperature field is then applied for UHI assessment using the first order reliability methods (MVFOSM and FORM). The results indicate that although the maximum intensity of UHI occurs in the warm months, there is a higher probability for UHI formation in the cold months. Furthermore, it is more probable that UHI forms during the night. UHI formation probabilities indicate that two districts in the central part of the city, mainly composed of old dense buildings, are more exposed to UHI in the warm and the cold months. District 1 that has the lowest probability of UHI formation is located in the most elevated part of the city (close to the Alborz mountain range). Results are invaluable for policy making process and risk management plans to assess severity levels of UHI in different regions based on the probability of event's occurrence.

1. Introduction

Global temperature has been increasing and is expected to continue rising in the future as a consequence of anthropogenic activities (Stern, 2006). Also, it should be noticed that population growth exacerbates the impacts of global warming. The percentage of the world's population living in urban areas has been increasing (United Nations, 2014). The rapid growth of urbanization and the expansion of the human-made structures as a replacement of the natural cover (e.g. vegetation) is one of the main causes of climate change (Streutker, 2002; Touchaei and Wang, 2015). Furthermore, urbanization can increase the intensity of extreme events such as heat waves (Lin et al., 2018).

Urbanization can directly affect heat islands (HI) formation in municipal areas, which is generally called urban heat island (UHI). Urbanization transforms natural landscapes into impervious covers and urban infrastructures. This transformation reduces the vegetation cover and transpiration, increases solar radiation absorption, and thus enhances UHI (Greater London Authority, 2006; Yao et al., 2017; Morabito et al., 2016). This phenomenon was first evaluated in the city of London in 1818 (Howard, 1818). UHI can be described as regions

with greater temperature than their rural neighbors (Estoque et al., 2017). UHI has been observed in both large and small cities. Although studies have demonstrated that UHI formation is independent of the city size, its effect often reduces as city size decreases [Oke, 1973; Oke, 1982; Aniello et al., 1995; EPA (US Environmental Protection Agency), 2008]. The magnitude of UHI depends on the building density in that region, the percentage of green spaces, materials used in the urban fabric, urban canyon characteristics, and the anthropogenic heat (Oke et al., 1991). UHI has a direct impact on energy consumption, and it can lead to increase of pollutants, which can cause health problems for children and elderly adults (Cartalis et al., 2001; Hassid et al., 2000; Santamouris, 2001). In addition, UHI can affect atmospheric circulation such as the sea breeze in the cities near the coast (Shen et al., 2018). Moreover, UHI and heat waves as the extreme meteorological events impact the people with cardiovascular diseases (Lenzuni et al., 2009; Lo and Quattrochi, 2003; Reid et al., 2009; Tomlinson et al., 2011; Wang et al., 2009).

UHIs can be considered in two groups including surface UHI and atmospheric UHI. Surface UHIs are evaluated based on land surface temperature (LST), whereas atmospheric UHIs are assessed by the air

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<https://doi.org/10.1016/j.atmosres.2019.03.038>

Received 4 November 2018; Received in revised form 28 March 2019; Accepted 29 March 2019

Available online 01 April 2019

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temperature. They are generally categorized into canopy layer UHIs and boundary layer UHIs (EPA (US Environmental Protection Agency), 2008). Air temperature data are usually obtained from meteorological stations, but due to their sparse distribution, the spatially-continuous analysis is often difficult to be conducted (Shen et al., 2016). An insufficient number of meteorological stations could not represent atmospheric changes and thus they are not appropriate for climate studies in urban areas (Merbitz et al., 2012; Chang et al., 2010; Honjo et al., 2015; Chen et al., 2016a, 2016b). As meteorological stations are often sparsely distributed and they usually do not have sufficient data records, LST data are the most common resource to study UHI. Many studies have used remote sensing and satellite data to evaluate the relationship between LST and UHI characteristics in recent years (e.g., Tomlinson et al., 2011; Chun and Guldmann, 2014; Hu and Brunsell, 2015; Bokaie et al., 2016; Amanollahi et al., 2016; Estoque et al., 2017).

Remote sensing is a useful tool to evaluate UHIs, but lack of required spatial and temporal resolution from satellite products can affect a robust analysis. Noise and uncertainties in remote sensing data are other problems that should be considered. Cloud is one of the main hindrances in remote sensing to provide a long continuous record of data such as LST (Amanollahi et al., 2016). Numerical models such as WRF (Weather and Research Forecasting) can be also used for assessing UHI (Chen et al., 2014; Morini et al., 2018). Although simulations by the WRF model need high computational cost and time, the model can produce a long record of the hydrometeorological variables like temperature in the fine temporal and spatial resolution, which is required for a complete assessment of the UHI characteristics. In the past few years, many researchers have used the WRF model separately or coupled with other models (e.g. statistical method) to characterize UHI (e.g., Chen et al., 2004; Kusaka et al., 2009; Giannaros et al., 2013; Chen et al., 2014; Bhati and Mohan, 2016; Li et al., 2017; Morini et al., 2018; Liu et al., 2017; Giannaros et al., 2018).

Spatial and temporal variation and intensity of the UHI have been investigated in small and large cities. Doyle and Hawkins (2008) showed that the intensity of the UHIs is more substantial during the night, which agrees with the results reported by the EPA (US Environmental Protection Agency) (2008). Founda et al. (2015) also demonstrated that UHI has a different pattern during the night compared to the daytime. Past studies showed that the seasonal intensity of UHI has different patterns. For instance, Yang et al. (2013) assessed the UHI intensity in Beijing and illustrated that UHI is more significant in fall and winter. Similarly, Souch and Grimmond (2006) reported that UHIs are weaker in the summer. Conversely, Giannaros and Melas (2012) and Tan and Li (2015) stated that UHI is more severe in summer compared to winter. Recently, Giannaros et al. (2018) examined the sensitivity of the spatiotemporal characteristics of the UHI to the modified WRF surface temperature. Their results signified that the surface and urban canopy properties of the model strongly affect the model performance in characterizing UHI in the greater Athens area. Their findings are consistent with the research previously conducted by Liu et al. (2017) in the city of Beijing in China, where they showed that the urban surface characteristics impact the output meteorological variables of the WRF model.

Land surface temperature (LST) and air temperature data are mostly presented in a coarse resolution. To better investigate UHI or any other heat-related phenomenon for valid and efficient management, LST or air temperature fields need to be downscaled to a finer resolution. Statistical or dynamical methods can be used to improve the resolution of the model data. Due to time and computational efficiency of the statistical methods, they are widely used in many studies (e.g., Zekšek and Oštir, 2012; Mukherjee et al., 2015; Bonafoni, 2016; Moghim and Bras, 2017; Moghim and Bras, 2019). For instance, image fusion, spatial sharpening, disaggregation, and artificial neural network are the most common downscaling approaches (Zekšek and Oštir, 2012). Although many studies have examined different temperature downscaling approaches, few included field downscaling of temperature. Recently,

Zerenner et al. (2016) used a multi-objective genetic programming framework to downscale 10 m temperature fields of COSMO (Consortium for Small Scale Modeling) model (Baldauf et al., 2011) from 2800 m to 400 m grid resolution.

This study uses a proper downscaling method for the model output, WRF-ARW (Advanced Research Weather) temperature field. This method is able to downscale 2 km temperature field to a 50 m grid spacing. Furthermore, this work evaluates the temporal and spatial characteristics of UHI in the city of Tehran using a probabilistic approach. UHI assessment in the developed probability framework enables us to compare 22 different districts of the city. Although temporal and spatial characteristics of UHI have been investigated in many studies, to the best knowledge of the authors, this is the first work that uses reliability methods with a numerical model to evaluate UHI. This study aims to use first order reliability methods to evaluate UHI in the city of Tehran. Reliability frameworks can consider the uncertainties (related to the parameters and modeling process) in the evaluation of UHI. Thus, the results can be properly used by decision makers for emergency action plans in the area that is highly endangered. To define a reliability framework for UHI evaluation, this article introduces the study domain in Section 2 and explains methodology in Section 3, followed by the results and conclusions in Sections 4 and 5, respectively.

2. Study domain

Tehran (capital of Iran) is located in the northern part of Iran in the vicinity of Alborz Mountains. The city is situated within the longitudes of 51° to 51° 40' E and latitudes of 35° 30' to 35° 51' N (Fig. 1). Tehran is the most populated city in Iran with a population of 8,693,706 people based on Iranian population and housing census in 2016 (Statistical Center of Iran, 2016).

Fig. 1 shows that the city elevation is extended from 1032 m to over 2000 m. The average temperature recorded by the meteorological stations from 1995 to 2016 is 16–19°C. The topography of the region causes the variability of the temperature and also the precipitation. For instance, annual precipitation has been reported 422 mm and 145 mm in the northern and southeast parts, respectively (Habibi and Hourcade, 2005). This study uses 2 m air temperature of three meteorological

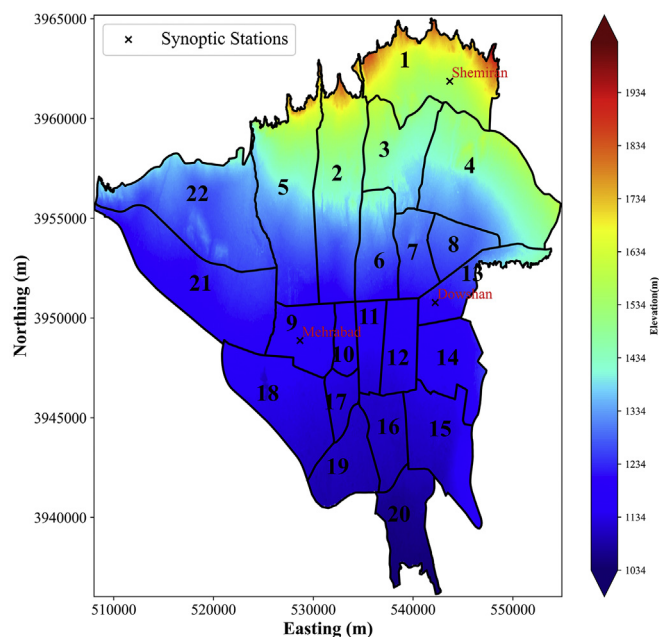


Fig. 1. Tehran's DEM, selected synoptic stations, and districts. Numbers refer to the districts of Tehran. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
General characteristics of the stations in Tehran including Mehrabad, Shemiran, and Dowshan.

Station	Latitude	Longitude	Elevation (m)
Mehrabad	35°41'N	51°19'E	1190.8
Shemiran	35°48'N	51°29'E	1549.1
Dowshan	35°42'N	51°20'E	1209.2

stations of Mehrabad, Shemiran, and Dowshan (cross symbols in Fig. 1) for calibration and validation of the downscaling model. The characteristics of the stations are listed in Table 1. The selected stations can adequately cover the study domain and take into account the topographic differences in the developed model.

3. Methodology

3.1. Downscaling WRF-ARW temperature field

WRF-ARW version 3.7.1 (Skamarock et al., 2008) is used to derive the initial air temperature field at 2 m elevation. As demonstrated in Fig. 2, a three one-way nested domain with a scaling ratio of 1:3 is used. The exterior domain has an 18 km grid spacing with a mesh consisting of 109×145 points. The second domain has a grid spacing of 6 km and is composed of 55×55 grid points. The innermost domain comprises a mesh with 55×55 grid points with 2 km spacing, which adequately covers the city of Tehran and its surrounding rural areas.

This study uses WRF single moment six-class scheme (Hong et al., 2004; Hong and Lim, 2006) for the microphysics, the rapid radiative transfer model longwave radiation scheme (Mlawer et al., 1997) and Dudhia shortwave radiation scheme (Dudhia, 1989) for radiation processes. Monin-Obukhov scheme (Monin and Obukhov, 1954) and Yonesi University layer scheme (Noh et al., 2003) are also applied for the surface layer and planetary boundary layer physics, respectively. Kain-

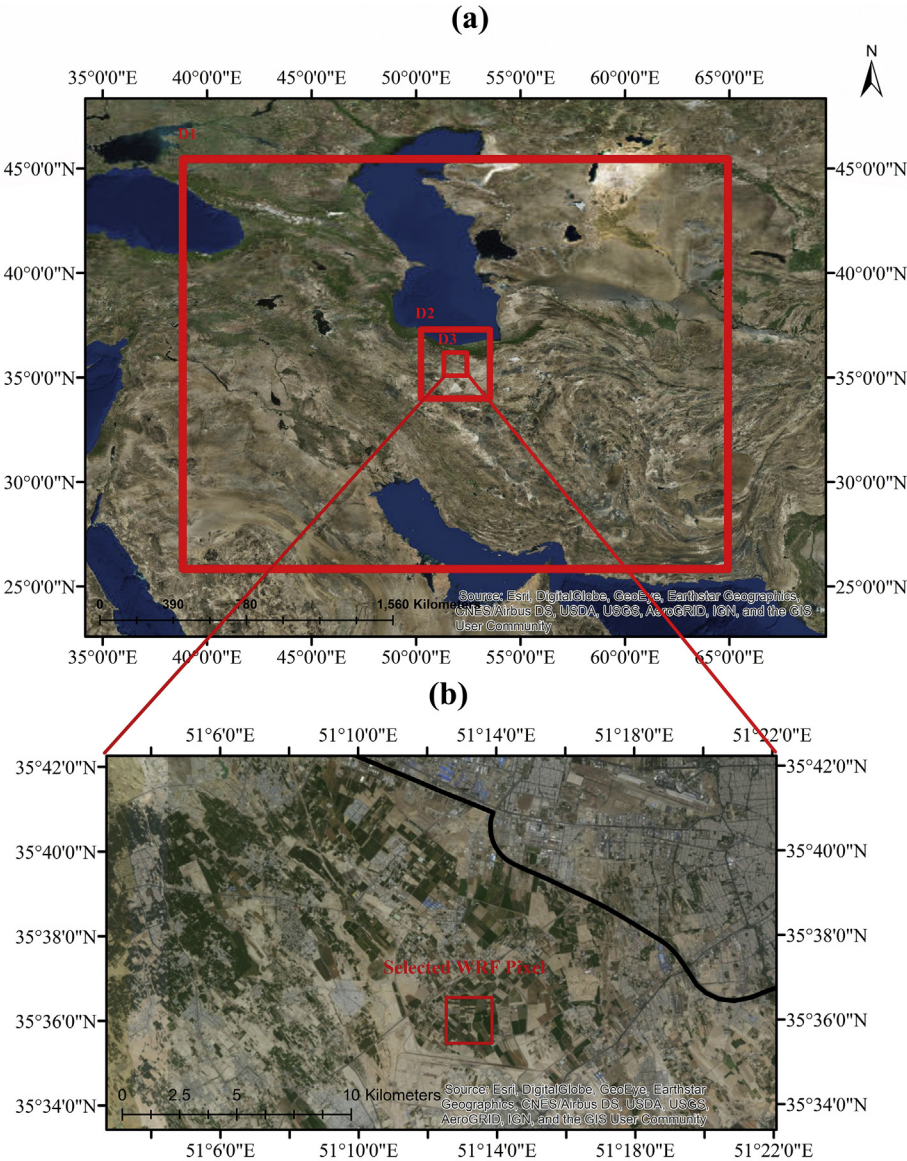


Fig. 2. (a) WRF one-way three nested domains. D1, D2, and D3 (red squares) illustrate the three nested domains. D3 is the innermost domain covering the study area (Tehran) and (b) the selected WRF pixel in the rural area (shown by the red square) (obtained from ESRI). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fritsch scheme (Kain, 2004) is selected for parameterizing cumulus convection. All the physics schemes are similar for all domains. The National Center for Environmental Prediction (NCEP) Global Forecast System (GFS) Final Analyses data with the horizontal resolution of $1^\circ \times 1^\circ$ and 6 h temporal resolution is used for the initial and lateral boundary conditions. The model runs for the whole year of 2012 to cover both cold and warm seasons. In this paper, January, February, and December are referred to as cold months and June, July, and August are considered as warm months. Since the hourly 2 km temperature output from the WRF is not a sufficient resolution for authentic decision making processes, therefore the temperature field needs to be downscaled to a finer resolution.

Temperature data from synoptic stations (Mehrabad, Shemiran, and Dowshan) are used as observations to validate the downscaling model. After a trial and error procedure, air temperature at the elevation of 2 m (T_a) and the surface water vapor mixing ratio (Q_v) were obtained as the best model predictors. These candidates for downscaling the temperature field had the most correlation with the temperature recorded at the synoptic stations and also the correlation matrix of these parameters indicated that they do not cause multicollinearity.

3.1.1. Primary downscaling using inverse distance weighting (IDW)

To generalize the downscaling model, selected variables (T_a , Q_v) are re-gridded to the synoptic stations using an inverse distance weighting (IDW) interpolation method, resulting in T_a^{IDW} and Q_v^{IDW} . The general form of IDW to estimate a variable ($f_{x,y}$) can be expressed as Eq. (1) (Bartier and Keller, 1996):

$$f_{x,y} = \frac{\sum_{i=1}^N f_i W_i}{\sum_{i=1}^N W_i} \quad (1)$$

where N is the number of the samples, f_i is the i^{th} variable value. W_i is the weight of the i^{th} sample in the interpolation procedure defined as Eq. (2) (Bartier and Keller, 1996):

$$W_i = d_{x,y,i}^{-\beta} \quad (2)$$

where $d_{x,y,i}$ is the distance between estimation point and the location of the i^{th} sample and β is an exponent set to be 2, which is typically used (Ozelkan et al., 2015; Valent and Vyleta, 2015). An increase in β reduces the effect of the points that have a large distance to the estimation point (Lloyd, 2005). The general procedure of the downscaling method used in this study is illustrated in Fig. 3.

3.1.2. Bayesian regression model

One of the common approaches for statistical downscaling is linear regression, which can be expressed as Eq. (3) (Bolstad and Curran, 2017):

$$y = \theta_1 x_1 + \dots + \theta_k x_k + \varepsilon \quad (3)$$

where y is the model response (regressand), θ_i are model parameters, x_i are explanatory variables (regressor), and ε is the model error. The model parameters in Eq. (3) form a hyperplane in the $(k+1)$ space. Considering all observation samples and its associated regressors, Eq. (3) can be rewritten as (Bolstad and Curran, 2017):

$$\mathbf{Y}_{n \times 1} = \mathbf{X}_{n \times k} \boldsymbol{\theta}_{k \times 1} + \boldsymbol{\varepsilon}_{n \times 1} \quad (4)$$

where n is the number of samples. $\boldsymbol{\theta}_{k \times 1}$ can be obtained by minimizing the summation of the squared difference between model estimations and the observations (least square error). Hence (Bolstad and Curran, 2017):

$$\|\boldsymbol{\varepsilon}_{n \times 1}\|^2 = \varepsilon_1^2 + \dots + \varepsilon_n^2 \quad (5)$$

$$\hat{\boldsymbol{\theta}}_{k \times 1} = \operatorname{argmin}(\|\boldsymbol{\varepsilon}_{n \times 1}\|^2) = \operatorname{argmin}(\|\mathbf{Y}_{n \times 1} - \mathbf{X}_{n \times k} \boldsymbol{\theta}_{k \times 1}\|^2) \quad (6)$$

where $\hat{\boldsymbol{\theta}}_{k \times 1}$ represents the point estimate vector for the model parameters, which also can be expressed as (Bolstad and Curran, 2017):

$$\hat{\boldsymbol{\theta}}_{k \times 1} = (\mathbf{X}_{n \times k}^T \mathbf{X}_{n \times k})^{-1} \mathbf{X}_{n \times k}^T \mathbf{Y}_{n \times 1} \quad (7)$$

$$s^2 = \frac{1}{n-k} \boldsymbol{\varepsilon}_{n \times 1}^T \boldsymbol{\varepsilon}_{n \times 1} \quad (8)$$

where s^2 is the variance of the error.

The Bayesian regression model provides a probability distribution for its parameters and the variance of the error. Therefore, this work uses the Bayesian model to consider uncertainties in the model and provide probabilistic results that can be used in a reliability framework. First, the uniform priors have been selected for the model parameters and the posterior model parameters have a multivariate t-distribution, while the posterior distribution of the variance has an inverse chi-squared distribution with a degree of freedom (ν) equal to $n-k$ (Bolstad and Curran, 2017; Lange et al., 1989 and Gelman et al., 2013). Since the number of the samples (n) is much larger than the number of regressors (k), model parameters and error variance can be considered to have a normal distribution. The characteristics of these distributions are expressed in Eqs. (9)–(12) (Bolstad and Curran, 2017):

$$\mu_{\theta_i} = \hat{\theta}_i \quad (9)$$

$$\Sigma_{k \times k}^0 = s^2 (\mathbf{X}_{n \times k}^T \mathbf{X}_{n \times k})^{-1} \quad (10)$$

$$\mu_{\sigma} = s \quad (11)$$

$$\sigma_{\sigma}^2 = \frac{s^2}{2(\nu-4)} \quad (12)$$

where μ_{θ_i} is the mean of the i^{th} model parameter, $\Sigma_{k \times k}^0$ represents the covariance matrix of model parameters, μ_{σ} is the mean of the model errors' standard deviation, σ_{σ}^2 refers to the variance of the model error's standard deviation, and ν is the degree of freedom. To have a robust model, appropriate predictors should be chosen. To select a proper set of variables, the data sample set (about 7500 samples) is divided into two subsets including calibration and validation, where the calibration includes 60% of all data samples. The initial 55×55 (3025 pixels) grid is converted to a 2200×2200 grid (4,840,000 pixels), downscaling the air temperature field from a 2 km (WRF output) to a 50 m resolution. The developed downscaling method is referred to as the downscaling model through the rest of this paper. Three most common scale dependent measures are used to assess the downscaling model accuracy (Hyndman and Koehler, 2006) as defined in Eqs. (13)–(15):

$$\text{ME} = \frac{1}{n} \sum_{i=1}^n \varepsilon_i \quad (13)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\varepsilon_i| \quad (14)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n \varepsilon_i^2} \quad (15)$$

where ME is the mean error, MAE is the mean absolute error, and RMSE is the root mean square error. In the equations above, ε_i is the error (the difference between the observation and the downscaled WRF-ARW temperature in the pixel where the synoptic station is located).

3.2. Reliability methods (MVFOsm and FORM)

The developed downscaling method that combines IDW interpolation with a Bayesian regression model (Sections 3.1.1 and 3.1.2) not only provides the temperature field in a finer scale but also has the privilege of presenting the output temperature field probabilistically. Thus, MVFOsm (Mean Value First Order Second moment Method) and FORM (First Order Reliability Method) use the probabilistic outputs to evaluate the probability of the UHI formation. These methods can consider the uncertainties within the problem and hence the results can indicate different confidence and certainty levels.

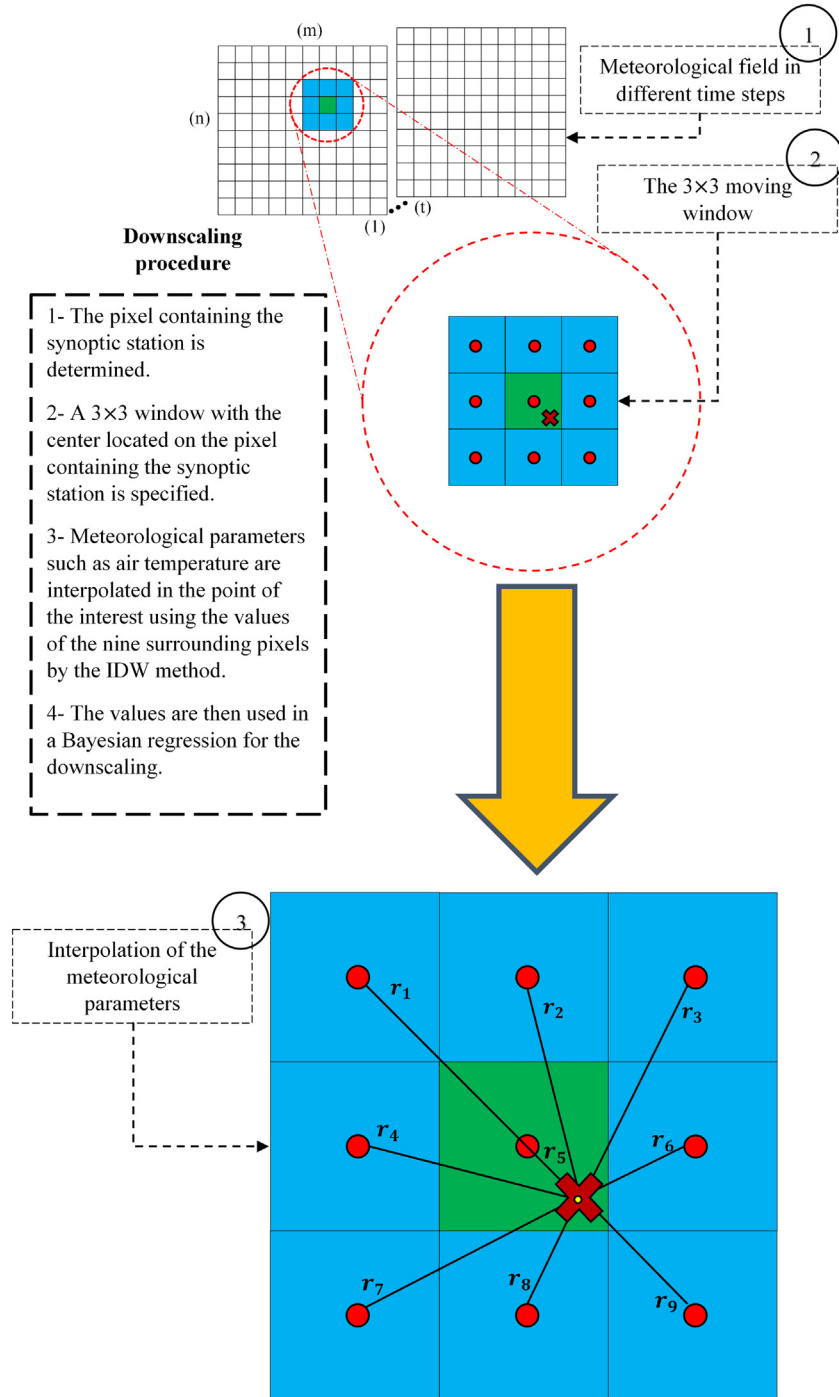


Fig. 3. The schematic diagram of the downscaling procedure.

3.2.1. MVFOSM evaluation

MVFOSM method is based on a first-order Taylor series approximation of the performance function linearized at mean values of the random variables. The method only uses the second moment of the random variables to estimate the reliability index of the performance function (Halder and Mahadevan, 2000). This study defines the performance function (Z) as Eq. (16):

$$Z(T_{rural}, \theta_1, T_a^{IDW}, \theta_2, Q_v^{IDW}, \theta_3, \epsilon) = T_{rural} - (\theta_1 T_a^{IDW} + \theta_2 Q_v^{IDW} + \theta_3 + \epsilon) \quad (16)$$

T_{rural} is the rural area temperature and the other six variables ($\theta_1, T_a^{IDW}, \theta_2, Q_v^{IDW}, \theta_3, \epsilon$) are the Bayesian regression parameters. A square area of 4 km² with the center placed at 51.22°E and 35.60°N is selected as

the rural region (see Fig. 2). This selected region is mostly covered by agricultural land (no urban land-use). All the variables in Eq. (16) are assumed to be random and normally distributed. Second moments of the performance function are defined as Eqs. (17) and (18):

$$\mu_Z = Z(\mu_{T_{rural}}, \mu_{\theta_1}, \mu_{T_a^{IDW}}, \mu_{\theta_2}, \mu_{Q_v^{IDW}}, \mu_{\theta_3}, \mu_{\epsilon}) = Z(\mathbf{M}_{7 \times 1}) \quad (17)$$

$$\sigma_Z = \nabla Z(\mathbf{M}_{7 \times 1})^T \Sigma_{7 \times 7} \nabla Z(\mathbf{M}_{7 \times 1}) \quad (18)$$

where μ is the mean operator, $\mathbf{M}_{7 \times 1}$ is a vector including the mean values of the random variables used in the performance function, $\nabla Z(\mathbf{M}_{7 \times 1})$ is the gradient of function Z at the mean values, and $\Sigma_{7 \times 7}$ is the covariance function of the variables. Thus, the reliability index (β) is calculated as Eq. (19) (Halder and Mahadevan, 2000):

$$\beta = \frac{\mu_Z}{\sigma_Z} \quad (19)$$

MVFOSM is operated on each of 4,840,000 grid points for both cold and warm months with an hourly time step covering the entire 24 h. In addition, the average reliability index for the city of Tehran is evaluated at each time step.

3.2.2. FORM evaluation

MVFOSM does not use the probability distribution of the variables and it utilizes the linear approximation of the function. Thus, using MVFOSM in this study with a nonlinear performance function Z can cause errors (Haldar and Mahadevan, 2000). To better evaluate the reliability of UHI formation, this study also uses FORM. However, because of the complexity and excessive computational time demands, FORM evaluation is only applied to the time step when MVFOSM resulted in the maximum average reliability index. In the FORM, all random variables used in the performance function should be evaluated in the standard normal space. The variables from normal ($\mathbf{x}_{7 \times 1}$) can be transformed to the standard normal space ($\mathbf{u}_{7 \times 1}$) as Eq. (20) (Der Kiureghian et al., 2005):

$$\mathbf{u}_{7 \times 1} = \mathbf{L}_{7 \times 7}^{-1} \mathbf{D}_{7 \times 7}^{-1} (\mathbf{x}_{7 \times 1} - \mathbf{M}_{7 \times 1}) \quad (20)$$

where $\mathbf{D}_{7 \times 7}$ is the diagonal matrix of the standard deviations and $\mathbf{L}_{7 \times 7}$ is the Cholesky decomposition of the correlation matrix ($\mathbf{R}_{7 \times 7}$). Thus, the original space can be expressed as Eq. (21) (Der Kiureghian et al., 2005):

$$\mathbf{x}_{7 \times 1} = \mathbf{M}_{7 \times 1} + \mathbf{D}_{7 \times 7} \mathbf{L}_{7 \times 7} \mathbf{u}_{7 \times 1} \quad (21)$$

The general algorithm of FORM is demonstrated in Fig. 4. The gradient of the performance function and its norm can be calculated as Eqs. (22) and (23) (Der Kiureghian et al., 2005):

$$\mathbf{G}_{7 \times 1} = [\nabla Z(\mathbf{x}_{7 \times 1})^T \mathbf{D}_{7 \times 7} \mathbf{L}_{7 \times 7}]^T \quad (22)$$

$$n_G = \|\mathbf{G}_{7 \times 1}\| \quad (23)$$

where $\mathbf{G}_{7 \times 1}$ is the gradient vector of function Z in the standard normal space, and n_G is the norm of the vector $\mathbf{G}_{7 \times 1}$. Alpha vector ($\alpha_{7 \times 1}$) and the new trial point of the standard normal space are then calculated as Eqs. (24) and (25) (Der Kiureghian et al., 2005):

$$\alpha_{7 \times 1} = -\mathbf{G}_{7 \times 1} / n_G \quad (24)$$

$$\mathbf{u}_{7 \times 1}^{\text{new}} = \left(\frac{\mathbf{G}_{7 \times 1}}{n_G} + \alpha_{7 \times 1}^T \mathbf{u}_{7 \times 1}^{\text{old}} \right) \alpha_{7 \times 1} \quad (25)$$

The process is repeated until the convergence criteria are met. The convergence is achieved when the following inequalities are satisfied (Haldar and Mahadevan, 2000):

$$\left| \frac{Z(\mathbf{u}_{7 \times 1}^{\text{new}})}{Z(\mathbf{M}_{7 \times 1})} \right| < e_1 \quad (26)$$

$$\|\mathbf{u}_{7 \times 1}^{\text{new}} - \mathbf{u}_{7 \times 1}^{\text{old}}\| < e_2 \quad (27)$$

where e_1 and e_2 are constant (0.001). If the convergence is achieved, the reliability index and related probability are computed as Eqs. (28) and (29):

$$\beta = \alpha_{7 \times 1}^T \mathbf{u}_{7 \times 1}^{\text{new}} \quad (28)$$

$$p_f = \Phi(-\beta) \quad (29)$$

where Φ is the normal cumulative density function (CDF) and p_f is the probability of failure. In other words, p_f shows the probability of observing a higher temperature in each pixel located in the urban area compared to the temperature of the selected rural area. Thus, p_f can be considered as the probability of the heat island formation and can be used to assess its characteristics.

3.3. Heat island assessment

FORM is applied to each pixel located in the city of Tehran. The method is used for both warm and cold months in their selected time steps. Average probability is then calculated for each district (22 districts) in Tehran to investigate the possible relationship between UHI formation probability and physical features of the region including topography, wind field, and land cover.

4. Results and discussion

4.1. Downscaling validation

The regression parameters are calculated based on Eqs. (3)–(12) (Table 2). The results show that the standard deviation for θ_2 is 27.90, which is relatively large. An ordinary regression ignores the standard

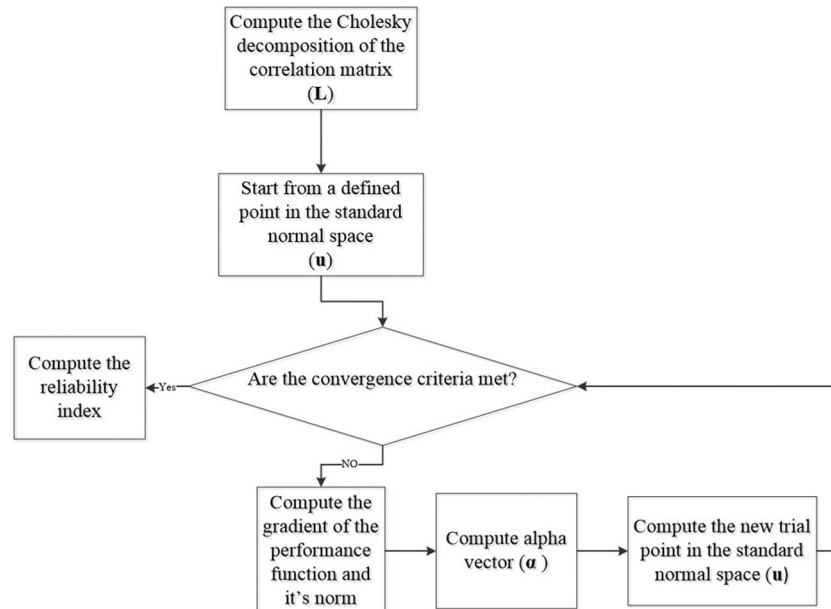


Fig. 4. The schematic diagram of the FORM algorithm.

Table 2
Statistics of the Bayesian regression parameters (Eqs. (3)–(12)). μ_{θ_i} and σ_{θ_i} are associated with the mean and the standard deviation of the i^{th} parameter of the Bayesian regression.

Parameter	Value
$\mu_{\theta_1}, \sigma_{\theta_1}$	0.93, 0.00
$\mu_{\theta_2}, \sigma_{\theta_2}$	−271.46, 27.90
$\mu_{\theta_3}, \sigma_{\theta_3}$	23.18, 1.04

Table 3
The statistical measures including RMSE, MAE, and ME for the estimated temperature from the WRF output and downscaling model (DS) for both warm and cold months.

Seasonal Average	RMSE		MAE		ME	
	WRF	DS	WRF	DS	WRF	DS
Cold Months	4.71	3.07	3.9	2.31	3.73	2.69
Warm Months	2.16	2.15	1.67	1.61	0.57	0.3

deviation of the parameters and thus can make errors. The statistical measures including average ME, MAE, and RMSE (Eqs. (13)–(15)) are calculated for the estimated temperature from the WRF output and downscaling model in all available stations for both warm and cold months (Table 3). WRF like other numerical models is biased in both warm and cold months. However, results showed that the temperature field is more biased in cold months (a warm bias), which is consistent with the results reported by García-Díez et al., 2013. Furthermore, results indicate that in both warm and cold season the downscaling method outperforms the WRF-ARW results. In other words, the developed downscaling method can improve the results in warm and cold months during the entire period (calibration and validation). The performance of the developed downscaling method is shown by the scatterplot (Fig. 5). The results illustrate that all estimations are mostly placed among the two upper and lower error bounds, which are 1.02 and 0.98 times of the exact values, respectively. This low

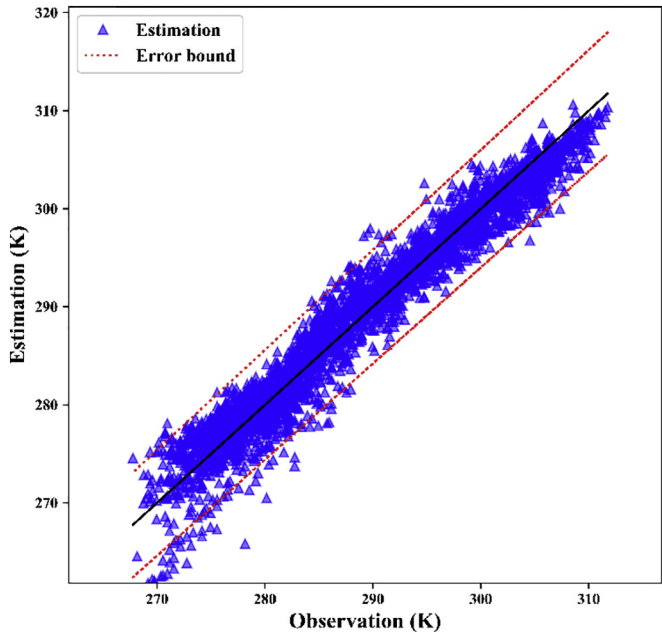


Fig. 5. Estimated (downscaled) vs observed temperature. Error margins are also depicted with the red dotted line.

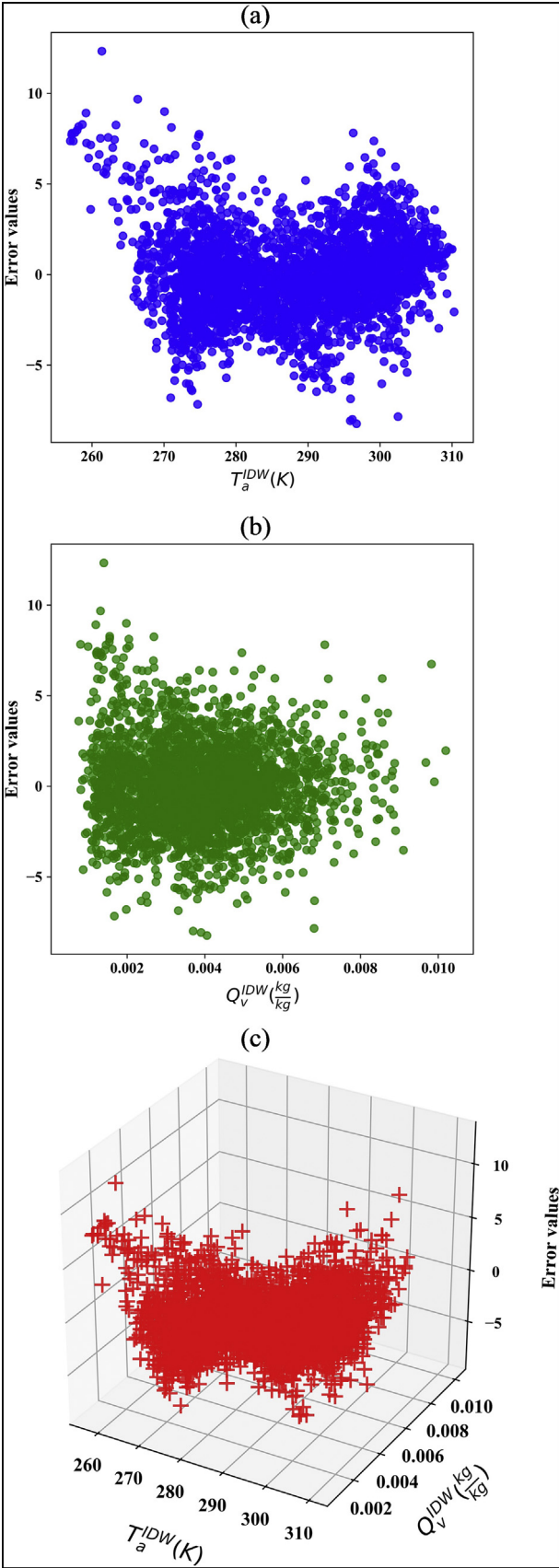


Fig. 6. Error values of the downscaling method vs (a) T_a^{IDW} , (b) Q_v^{IDW} , and (c) T_a^{IDW} and Q_v^{IDW} .

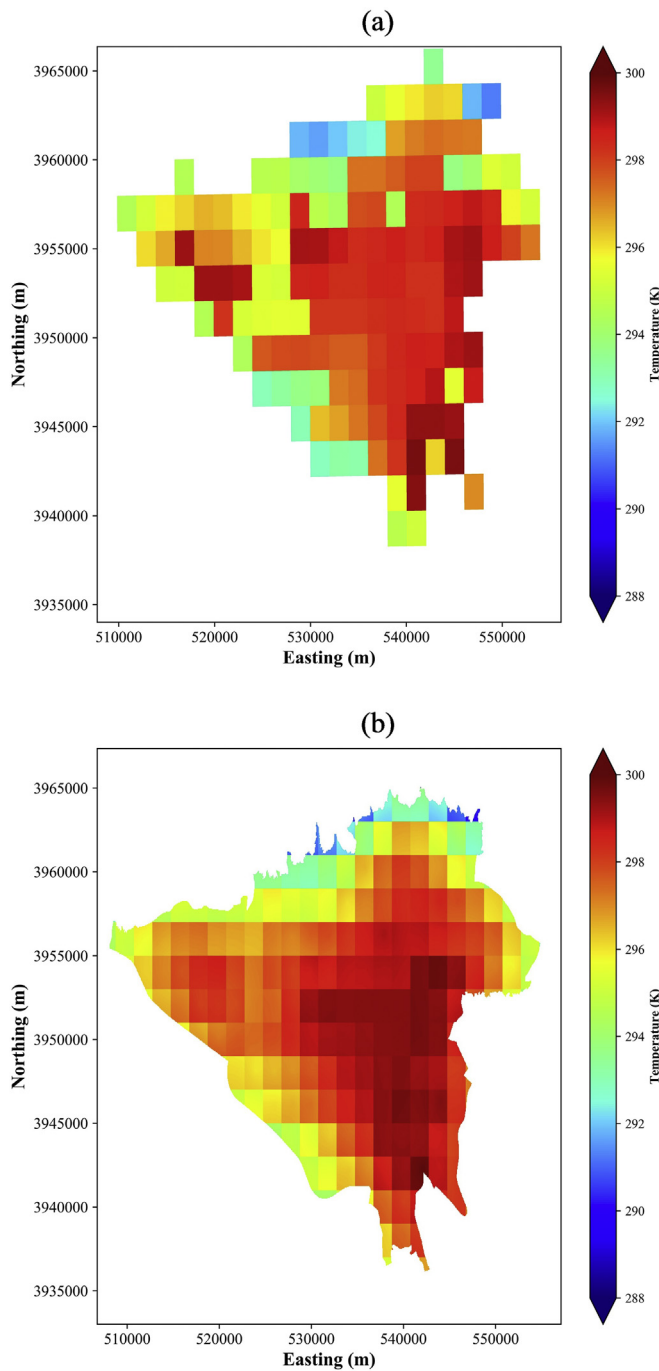


Fig. 7. (a) Tehran's air temperature field from WRF-ARW model and (b) Temperature field derived from the downscaling model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dispersion can confirm the validity of the developed downscaling method. Although the developed model works well in almost all range of temperature, its performance is reduced for temperatures less than 273.15 K (0 °C).

To better evaluate the performance of the developed model, heteroscedasticity of the errors is also checked for different values of the model predictors (T_a^{IDW} and Q_v^{IDW}) in Fig. 6. Fig. 6a (error values vs T_a^{IDW}) shows that the downscaling model has a similar performance for almost all ranges of T_a^{IDW} values except for T_a^{IDW} smaller than 273.15 K and the temperature ranges of 280 to 283 K. Fig. 6b (error values vs Q_v^{IDW}) illustrates that the model performs quite well for almost all

Q_v^{IDW} values. The 3D scatter plot of the regressors and error values is also shown in Fig. 6c. We can conclude that collinearity does not exist in the model and error values are not controlled by a single predictor.

To analyze the results, as an example, WRF-ARW air temperature field for the third day of June in the year 2012 at midnight is illustrated for the city of Tehran and its surroundings in Fig. 7a. There is a strong correlation between elevation and temperature gradient in the domain. Most of the heat (higher temperature) is concentrated in the middle area of the city (central business district, CBD). In other words, the CBD has trapped the heat in the atmosphere and consequently, this region is warmer than the rural area. Fig. 7b illustrates the downscaled temperature field of Fig. 7a to a 50 m grid spacing. We can see that the downscaled temperature can follow the pattern of the WRF temperature and also can maintain a smooth change in the temperature field.

4.2. Temporal evaluation of the UHI

The defined reliability index [Eq. (28)] can reflect the probability of the UHI formation [Eq. (29)]. A larger reliability index indicates a lower probability for UHI formation. To evaluate the reliability index (β), MVFOSM is applied on each time step of the downscaled temperature field in both cold and warm months [Eqs. (16)–(19)]. Diurnal cycle of average β for the whole city and for warm and cold months is illustrated in Fig. 8. Based on the performance function (Z), a larger β indicates a smaller probability of the UHI formation. The largest probability of the UHI formation (minimum average β) occurs at 2 and 4 AM (UTC) for warm and cold months, respectively. The results also show that UHI formation is more probable during the night and the early hours of the daytime. As the temperature rises, the reliability index increases as well. This indicates that even though the city is cooler during the night, the temperature difference is more significant between rural and urban areas. Note that although UHI is more severe during the night, the temperature difference between rural and urban area is also remarkable during the daytime and should be taken into account.

Furthermore, the results show that the smallest probability of the UHI formation (maximum average β) occurs at midday in both warm and cold months. Although a similar diurnal cycle can be observed in warm and cold months, their intensity is considerably different. In the

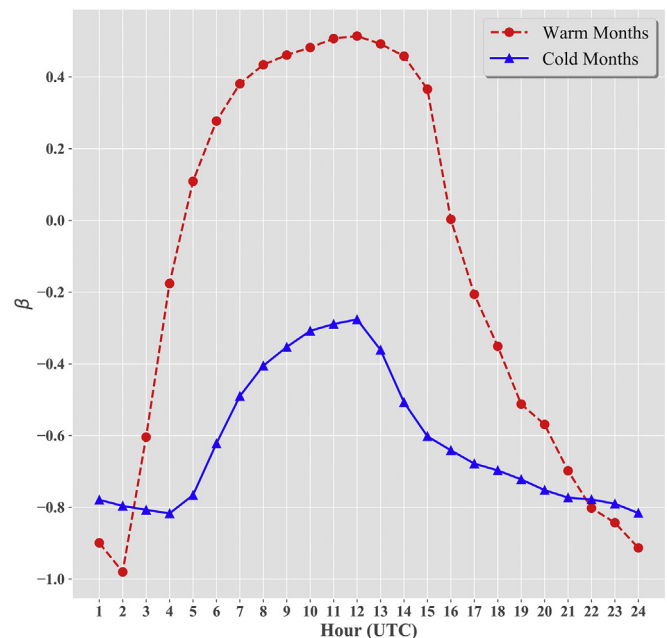


Fig. 8. Diurnal cycle of the average reliability index for the city of Tehran in warm (red dashed line) and cold (blue solid line) months in UTC.

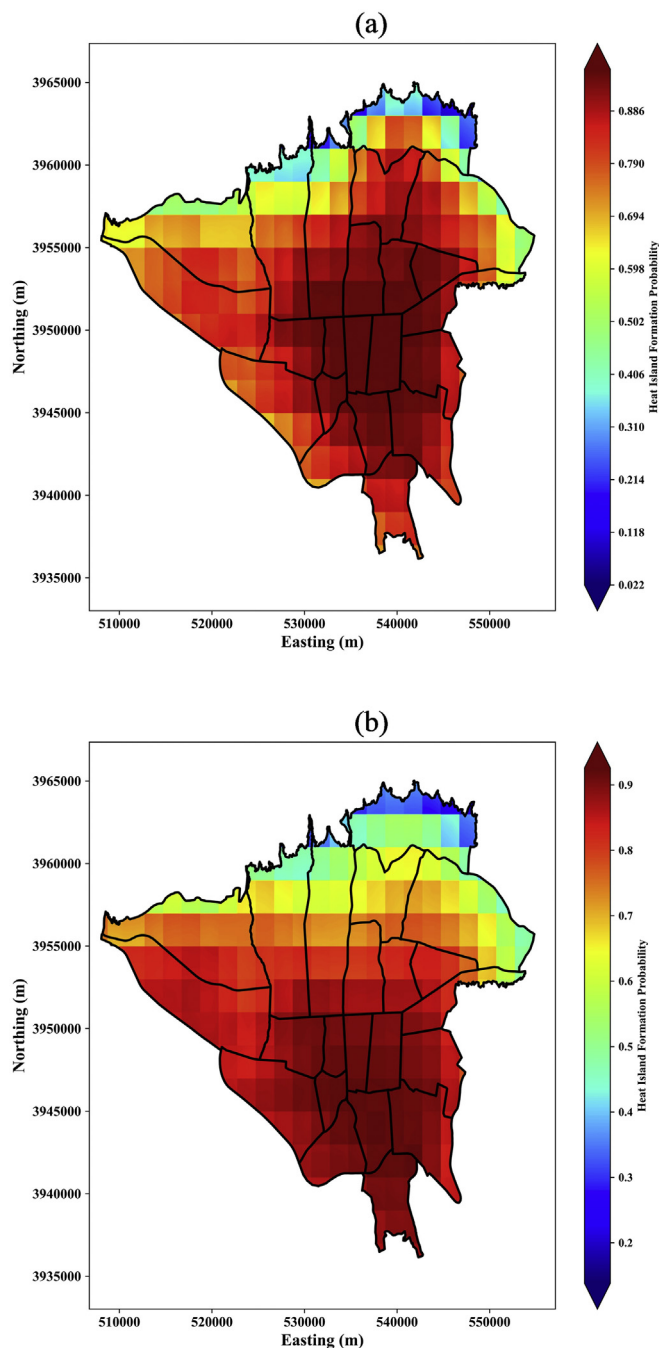


Fig. 9. Probability of heat island formation (p_f) for the city of Tehran in (a) Warm months at 2 AM (UTC) and (b) Cold months at 4 AM (UTC). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

warm season, a non-negative average β is observed from 5 AM to 4 PM, while in the cold season all average reliability indexes are negative. Results show that the UHI formation is more probable in cold months, which is consistent with the results of Yang et al. (2013) and Souch and Grimmer (2006). On average, summer has relatively smaller values of the minimum average β from 10 PM to 2 AM. Thus, we can conclude that the UHIs are most likely to form in the cold months, whereas the most severe ones occur in the warm season.

4.3. Spatial evaluation of the UHI

The diurnal cycle of the average reliability index was obtained using

MVFOSM. Due to high time and computational demands for conducting FORM, this method is only applied when the minimum average β occurs (2 and 4 AM for warm and cold months, respectively). Fig. 9 demonstrates the probability map of UHI formation for 2 AM in warm and 4 AM in cold months. For both assessed periods, a wide range of probability from larger values (in CBD) to smaller ones (in North) is observed. Indeed, our findings can reflect different features of varied areas in Tehran, which is in agreement with the results obtained by Bokaie et al. (2016).

The results illustrate that the heat in the warm months is trapped in the inner parts of the city (CBD) and it is extended to the north and the west areas (Fig. 9a). Also, the UHI is less likely to form in the border of the city. The higher probability of UHI occurrence (reddish colour) in the warm months shifts to the south in the cold months (Fig. 9b). In other words, there is a smaller probability to observe UHI in the north of the city in cold months relative to the warm months (Fig. 9b). The southern part of the city has a higher probability of exposure to UHI relative to the northern part in the cold months. Although the CBD is more exposed to UHI in both warm and cold months, the p_f associated with this area is higher during the warm season.

Varied exposure probability in the study domain shows that different parts of the city demonstrate a dissimilar response to UHI formation. The different response can be related to the physical features of the domain including the wind circulation (Miao and Chen, 2008; Chen et al., 2014) and the land cover of the city (Bokaie et al., 2016). To investigate this linkage, the average 10 m wind field of the WRF-ARW model and the MODIS Land Cover Type product (MCD12Q1) are assessed and compared with the obtained probabilities in the warm and cold months (Figs. 10 and 11, respectively).

Fig. 10 shows that the wind pattern and the circulation over the city are consistent with the obtained probability of the UHI formation. In other words, the regions where average wind velocity is relatively small (e.g., inner southern part), are most likely to have UHI (larger p_f). The topography of the city (mountain on the north side) causes a relatively small average wind velocity over the lower half of the city, where the most heat is concentrated, and thus UHI forms with high probability. On the other hand, northern parts with larger average wind velocity are less prone to UHI formation. We can conclude that wind and atmospheric circulation are important factors to increase or decrease UHI intensity. While high values for p_f in regions with large average wind velocities (e.g., north and north-west in Fig. 10) in the warm season can reveal that other factors can also play important roles in the UHI formation.

Another feature that affects UHI formation is the land cover. This study uses the 500 m global product of MCD12Q1 scheme five (Friedl et al., 2010) to classify land cover type in the city of Tehran. Land type is categorized into six groups including shrub, grass, cereal crops, broad-leaf crops, urban and built up, and sparse vegetation (Fig. 11). The results show that most of the city is considered urban and built up and only in scattered areas in west, northeast, and south sparse vegetation cover exists. The results confirm that the land cover type also follows our findings. The central area where it is mostly built up (heat is trapped and could not escape) has a higher p_f than other parts of the city. Dense concentrations of tall buildings in the CBD block the wind and prevent the circulation of the air. Conversely, the regions mostly covered by plantlike land type, have smaller p_f . As these parts are not enclosed with tall buildings and wind can circulate easily, heat is discharged efficiently out of these areas.

The average probability of heat island formation (p_f) for 22 districts of Tehran in warm and cold months is summarized in Table 4. The most critical condition (higher p_f) occurs in districts 12 and 16 for summer and winter, respectively. Districts 12 and 16 mostly encompass the old residential and business buildings with no plantlike land cover. These regions are one of the most polluted areas of the city, particularly during the winter. Both districts are located in the middle of the city with similar elevation. The high value of p_f in these two districts assures

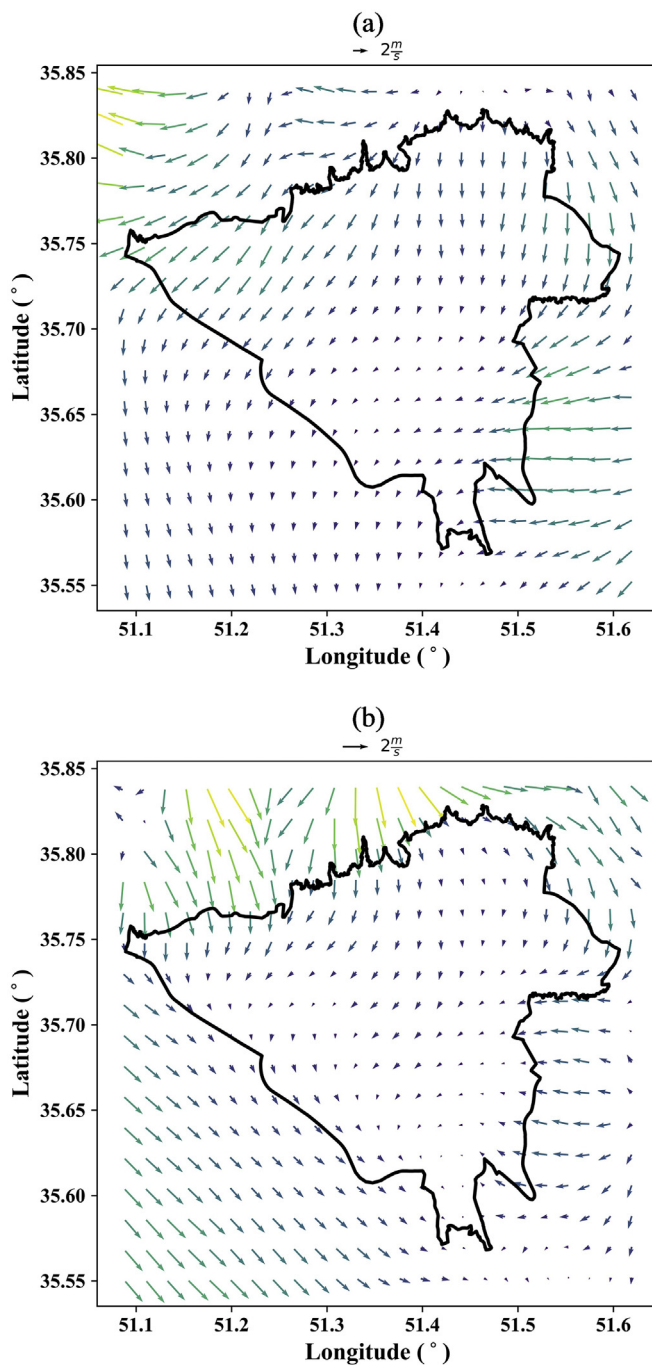


Fig. 10. Average 10 m wind velocity field in (a) Warm months at 2 AM (UTC) and (b) Cold months at 4 AM (UTC).

us that UHI forms considering all uncertainties (high confidence). The minimum p_f for both warm and cold months occurs in district one located in the northern part of the city with the maximum elevation (close to the Alborz mountain range). Most parts of this district with new texture encompass concentrated plant type.

District 22 ranks second in the summer and sixth in the winter for having the lowest p_f . This district includes Tehran's greatest botanic park and Chitgar Jungle Park, which is one of the recreational centers of the city. Furthermore, Table 4 indicates that although p_f in both periods are almost similar, 16 districts have greater p_f in the warm season relative to their cold season while only six districts have gained larger p_f in the cold months. The districts with greater p_f in cold months are located on a band extended from north-west to the south of the city.

These districts are located near the city borderline, which is close to the selected rural area. The results are consistent with the findings illustrated in Fig. 8, which demonstrates that the UHI formation is more probable in the cold months whereas the intensity seems to be higher in the summer.

To evaluate the impact of the topography of the region on the UHI formation, elevation of Tehran (from Digital Elevation Model, DEM) is classified into five groups (Fig. 12a). The average elevation of the classes from one to five is 1057 m, 1245 m, 1367 m, 1528 m, and 1821 m, respectively. Average values of p_f for each of the classes are depicted in Fig. 12b. Results confirm that there is a significant relationship between elevation and the probability formation of the UHI. In other words, the higher elevated area has a smaller chance of exposure to the UHI. This inverse correlation is more remarkable in the cold months. This signifies that during cold months the UHI formation is more affected by the topography of the region compared to the warm months.

5. Conclusions

This study used a statistical method to downscale WRF-ARW air temperature field. The developed method not only downscales the temperature field from a 2 km grid spacing to 50 m grid but also improves errors of the WRF-ARW model outputs. The downscaling method that combines IDW interpolation with a Bayesian regression model can adequately construct a 50 m temperature field. Using WRF to create a fine resolution of simulations has limitations (e.g. in numerical stability and computations). The simulation time depends on different factors (e.g. number of cores and time steps). On average, each monthly simulation with eight cores took about 50 h to complete. While the developed statistical downscaling method can reduce time, memory, and computational demands. In addition, this statistical method can present the downscaled temperature field probabilistically, which is useful for reliability and risk assessments. The air temperature field is produced hourly, which can be used as inputs to other hydroclimatological models. Since observations and satellite products are limited in temporal and spatial resolution.

The downscaled temperature field is combined with MVFOSM and FORM to assess UHI formation in a reliability framework in the city of Tehran (Capital of Iran). MVFOSM only uses the moments of the variables used in the failure function for the evaluation of the UHI formation. Hence, this method is only used for an initial assessment of UHI formation. The UHI formation probability is assessed by applying FORM on the time steps that minimum reliability indexes were obtained from MVFOSM. FORM uses the probability distribution of the failure function's variables for evaluating the associated formation probability. This is the first study to evaluate UHIs using reliability methods combined with a numerical model.

MVFOSM shows that the minimum reliability index (β) occurs at 2 AM and 4 AM (UTC) for warm and cold months, respectively. The minimum β refers to the maximum probability of the UHI formation. As the β value decreases, both the spatial extent and intensity of UHI increase. The results indicate that UHI is more probable to form during the night and the early hours of the morning. In addition, there is a greater probability for UHI formation in cold months relative to the warm months. Although generally, the average β index has a smaller value in the cold months, the minimum β occurs in the warm months. Thus, the most severe UHI occurs during the night and in the warm season.

The results show that the central part of the city (CBD) where most of the heat is trapped during the night, can be considered as the UHI core. The area, where the UHI is more probable to form, is mostly covered by the old residential houses. Also, this area includes multiple industrial sites and it has the most polluted air. Districts 12 and 16 with the highest average p_f can be considered as the UHI cores in the warm and cold months, respectively. Conversely, district 1 has the lowest

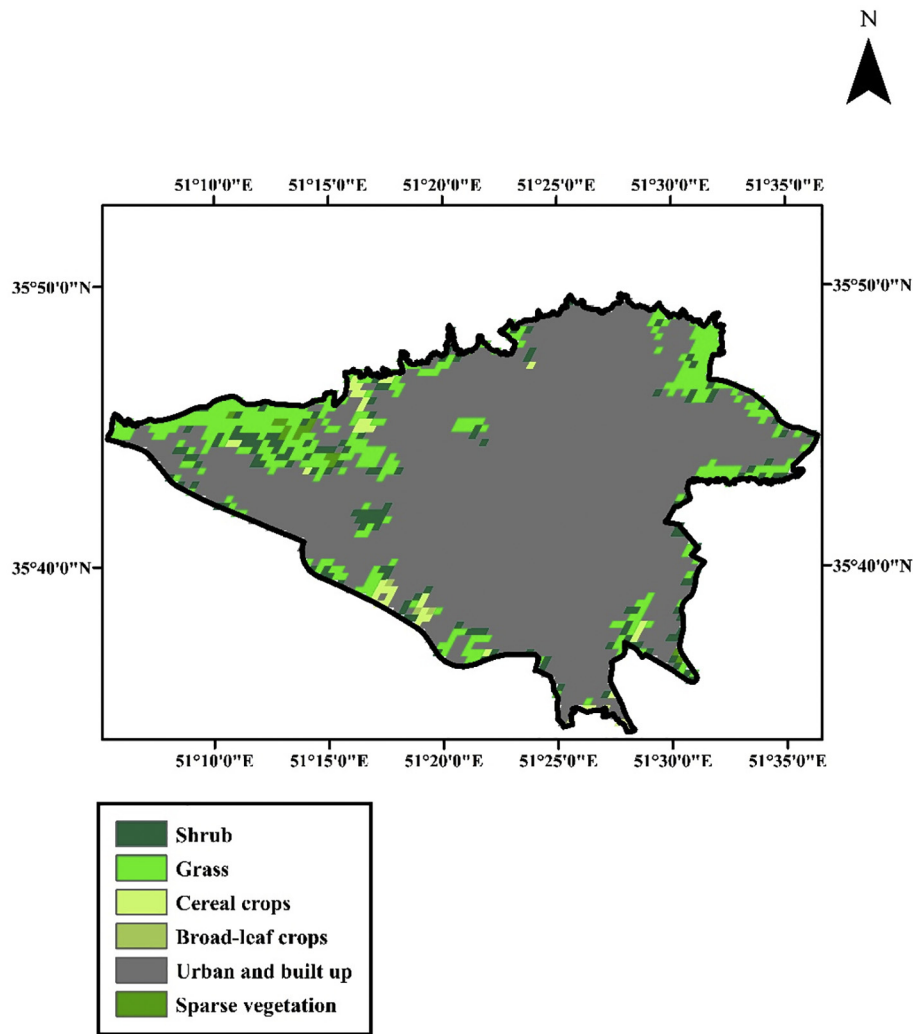


Fig. 11. Land cover classification (MCD12Q1 scheme five) with a 463 m resolution over Tehran.

Table 4
Probability of the heat island formation (p_f) in Tehran's districts during summer (2 AM UTC) and winter (4 AM UTC).

Summer (2 AM)		Winter (4 AM)
District	p_f	
1	0.516	0.448
2	0.756	0.690
3	0.860	0.671
4	0.741	0.649
5	0.699	0.708
6	0.938	0.817
7	0.947	0.839
8	0.931	0.823
9	0.916	0.893
10	0.955	0.909
11	0.958	0.908
12	0.961	0.907
13	0.865	0.795
14	0.918	0.878
15	0.908	0.893
16	0.943	0.920
17	0.932	0.915
18	0.819	0.876
19	0.862	0.899
20	0.862	0.902
21	0.803	0.838
22	0.695	0.751

average p_f . The results are consistent with the Tehran's land cover type. Districts with more plantlike cover have a lower p_f compared to the districts that are mostly surrounded by the urban land cover.

Furthermore, results showed that the topography of the region can affect the UHI formation, particularly in cold months, when the patterns of UHI formation probability and DEM are highly correlated. This can be due to the fact that Tehran's temperature field has a strong correlation with its elevation. The northern area of the city that is more elevated has a lower temperature relative to the southern part and the southern part is more exposed to UHI. Elevation also affects the air circulation and thus the wind flow. Wind and air motion have a major impact on both the intensity and spread of the UHI. The areas with larger p_f values are exposed to a weaker wind. Average wind velocity is observed to be more substantial in the warm season compared to the cold season. Northern areas of the city have relatively larger average wind velocities, so any concentrated heat can be discharged quickly, leading to a less probable UHI formation in these zones. Thus, the reliability method used for the UHI evaluation can consider the topography impact of the region on the UHI characteristics.

Results indicate that UHI condition is critical in most parts of the city and if appropriate mitigation actions do not apply, due to the population growth and the effects of global warming, people will face serious problems. An extreme heat-related phenomenon like UHI has devastating impacts on different sectors including environment, ecosystem, food, energy, and health system. The developed method provides a strong tool to assess the intensity of UHI including all associated

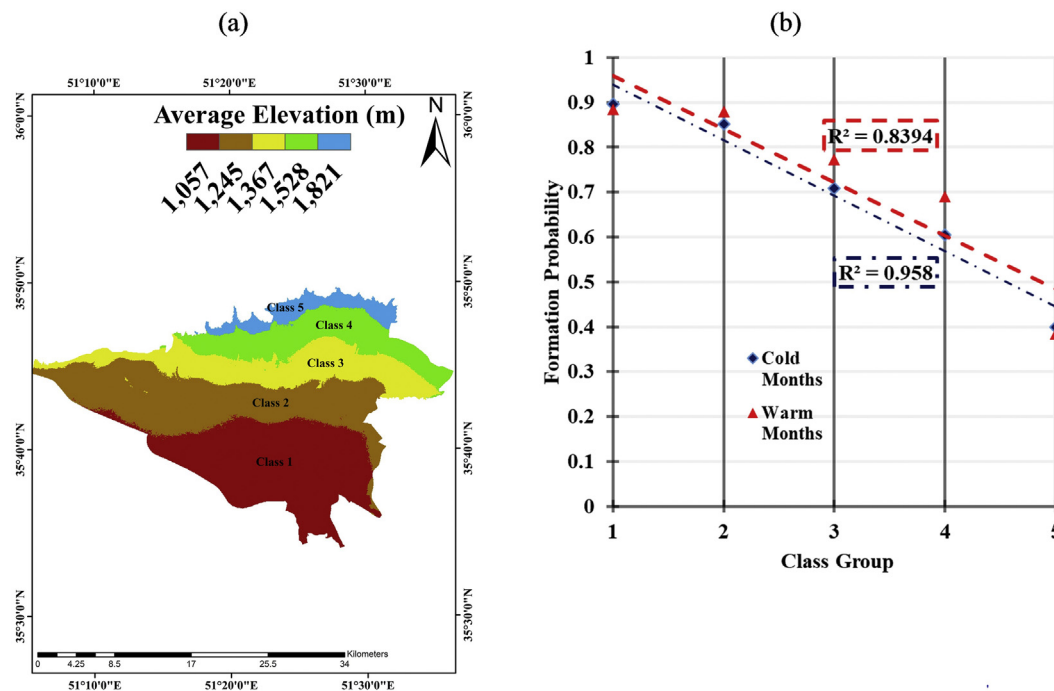


Fig. 12. Relationship between elevation and UHI formation: (a) DEM classification of Tehran into five classes (b) average formation probability of each DEM class. The fitted lines are shown by red dash and blue dash-dotted lines for warm and cold months, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

uncertainties, which is essential for decision makers. In addition, the method can cluster the region based on the severity levels of UHI formation, which is useful for efficient adaptation and mitigation management.

Acknowledgments

We thank the UNESCO Chair in Water and Environment Management for Sustainable Cities in Sharif University of Technology for their help in this research. We want to acknowledge Sharif University of Technology High Performance Computing (HPC) center for providing the computational resources.

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